Regional Crop Modeling:
How Future Climate May Impact Crop Yields in Switzerland

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Abstract
Crop yield levels and crop yield variability depend to a high extent on climate conditions. Due to climate change the local crop growth conditions in Switzerland are expected to change. This study addresses the question how weather, soil and management factors influenced mean wheat yield levels in twelve study regions in the Swiss Plateau during the period 1990 – 2008. In addition, we assess potential impacts of climate change on wheat yield levels and yield variability. Applying a multiple regression model based on historical yield, weather, soil and management data in the period 1990 – 2008 at a regional scale, we find clear relations between yield levels and weather as well as management and soil factors. We show that global warming is assumed to decrease wheat yield levels in all study regions between 4-10%. Nevertheless, negative impacts of climate change on wheat production can be minimized or even overcompensated if the CO_2 fertilization effect and possible adaptation measures are taken into account.

1. Introduction

1.1 Agriculture and Climate

Agriculture is an economic sector which depends highly on climatic conditions. On the one hand, radiation and temperature define together with crop characteristics and the atmospheric CO_2 concentration the potential yield for a crop in a specific region (Goudrian and Zadoks 1995). On the other hand, the attainable yield for the same crop and region can be derived from the potential yield if the local water and nutrient availability are considered (Goudrian and Zadoks 1995). The potential yield remains constant over the years for a given climate, soil and crop if breeding improvements are not taken into account. The attainable yield, however, changes from year to year, since weather conditions vary and farmers adapt their management practices according to the prevailing climate and market conditions. Also, weather influences the actual crop yields indirectly, as it has an impact on the expansion of diseases, pests, weeds, pollutants and calamities[1]. The understanding of the weather's and the climate's influence on crop yields is a field of interest for many agricultural stakeholders. For instance, for farmers it is important to know under which climatic conditions agricultural management measures (e.g. irrigation, pesticide and fertilizer applications, tillage operations) are necessary in order to prevent yield losses. The food industry wants to know how the current weather situation influences future yield levels in order to estimate future prices of agricultural goods. In addition, scientists and breeders investigate yield-weather relations in order to develop less climate-sensitive and regionally better adapted crop varieties.

Most recent studies investigating the impact of climate on yield levels focused on temperature and precipitation as explanatory variables (e.g. Lobell and Field 2007; Almaraz et al. 2008; Isik and Devados 2006; Flückiger and Rieder 1997). Besides the fact that these two variables are daily recorded by most weather stations and therefore easily accessible, temperature and water availability influence directly or indirectly many physiological processes in crops (Porter and

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[1] In this study the influence of weather and climate on the expansion of plant diseases, pests and weeds is not considered. Notwithstanding, climate and weather conditions a ect to a high degree yield damages caused by diseases, pests and weeds (Patterson et al. 1999).

Semenov 2005). Apart from temperature and precipitation, also solar radiation and relative humidity are important factors which determine crop yields (Hoogenboom 2000). In addition to the influence on yield levels, weather effects also crop yield quality. For wheat, for instance, the protein concentration in grains is known to be four times more dependent on climatic growth conditions than on variety (Spencer 1983). Yet in contrast to climate-yield relations, the impacts of weather on quality determining processes are much worse understood[2]. According to the Intergovernmental Panel on Climate Change (IPCC), most of the observed temperature increase since the middle of the 20th century was very likely caused by increasing concentrations of greenhouse gases resulting from human activity such as fossil fuel burning and deforestation (IPCC 2007). A changing global climate also signifies changing growing conditions for crops. According to Lobell and Field (2007) recent global temperature increases induced a reduction in global wheat, barley and maize yields. Possible consequences of climate change on agriculture can also be observed in Switzerland. For example, the drought in the year 2003 caused a reduction of average crop yields in Switzerland up to 20% (Keller and Fuhrer 2003). For Switzerland, a temperature increase in summer months of 1.4-4.7°C (median=2.7°C) is expected until the middle of the 21st century (Frei 2004). Projected alterations of precipitation in Switzerland in turn, depend highly on the season and the geographic region (Frei 2004). However, it is very likely that for all parts of Switzerland precipitation in summer will decrease (Frei 2004).

1.2   Modeling Climate Change Impacts on Agriculture

Most studies analyzing climate change impacts on agricultural systems use either process-based crop growth or regression models (Lehmann and Finger 2010). Process-based crop growth models simulate crop growth and crop yield levels by means of specific input variables (e.g. daily weather parameters, soil characteristics, crop characteristics, cropping system management options). Examples of recent crop growth simulation models are CropSyst (Stöckle et al. 2003), CERES (Ritchie et al. 1998), CROPGROW (Boot et al. 1998), EPIC (Williams et al. 1989) and WOFOST (Diepen et al. 1989). The main advantage of

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[2]   Crop quality is a multi-faceted and complex subject which depends on environmental conditions during plant growth and also on technology during harvest, storage and food processing (Porter and Semenov 2005).

crop growth simulation models is the explicit formulation of physiological plant processes (Finger 2009). Though a weakness is the uncertainty about these physiological processes and the sheer number of parameters in these dynamic and highly nonlinear models (Schlenker and Roberts 2008). Moreover, production and nutrient systems are often taken as exogenous variables in crop models which prevents the consideration for behavioral responses of farmers (Schlenker and Roberts 2008).

In contrast to crop models, regression models comprise adaptation actions taken by farmers to changes in climatic conditions and thus avoid the overestimation of negative climate change effects on crop production. A further advantage of regression models compared to crop simulation models is the flexibility of integrating management and policy factors as explanatory variables of yield levels besides weather and soil parameters. Moreover, regression models, in contrast to simulation models, use observed yield records as input data, meaning that a connection to the reality always is guaranteed[3]. Nevertheless, it should be taken into account that the validity of long-term projections of multiple regression models is severely restricted as new innovative adaption options cannot be considered. Therefore, only short-term forecasts should be made with multiple regression models.

Even though there are already numerous large scale and regional studies about multiple regression models estimating crop yields under future climatic conditions (Lobell and Field 2007; Osborne et al. 2007; Almaraz et al. 2008; Iglesias and Quiroga 2007; Reidsma et al. 2009), only little attention has been paid to the impact of climate changes on crop yields in Switzerland. However, large scale crop models cannot make significant statements about climate change impacts on crop yield levels in Switzerland, since the climatic conditions vary considerably within the Alpine region. The only published study, which used multiple regression models in order to estimate impacts of climate change on crop yield levels in Switzerland has been conducted by Flückiger and Rieder

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[3] A connection to observed crop yield levels in crop simulation models is only guaranteed if enough historical data for a detailed calibration of the model is available. However, this is often not the case.

(1997)[4]. Since then, new insights into climate change have been gained. Furthermore, recent studies investigating the impact of climate change on crop yields in Switzerland were all conducted for some specific sites (Torriani et al. 2007a; Torriani et al. 2007b; Finger 2011a), an integral approach for the whole Swiss Plateau, however, does not exist yet. Thus, this study aims to overcome this gap by developing of a multiple regression model for wheat yield levels in order to analyze yield-weather relations at a regional scale in the Swiss Plateau. Furthermore, we analyze integrally potential climate change impacts on regional wheat yields in Switzerland using historic yield and weather data as well as regional climate changes scenarios.

2. Material and Methods

2.1 Regression Model Design

We design a regression model at regional scale explaining average wheat yields by means of monthly weather parameters, a soil factor and some management variables as explanatory variables. In this paper we focus on wheat since it is the most important crop in Switzerland (SBV 2009). Besides climate variables, also management variables are included in the model in order to explain deviations in the average yield levels caused by systematic structural differences among the study regions and years. A similar approach has been done by Iglesias and Quiroga (2009), who used the engine power of farm equipment as proxy variable for technology and investment in a farm or in the farming sector of a district or country in order to account for large increases in crop productivity. Aside from weather and management characteristics, also soil properties affect crop yields. Particularly in the Swiss Plateau the soil conditions vary considerably. Therefore, for each study region, a soil factor is computed and integrated as explanatory variable into the regression model.

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[4] Flückiger and Rieder (1997) developed for the seven major crops in Switzerland multiple regression models on the basis of historical farm yield and monthly weather data. Neglecting the CO_2 fertilization effect they expected climate change to decrease the yield levels of the seven most important crops in Switzerland (Flückiger and Rieder 1997).

In order to smooth the dependent and explanatory variables, we use regionally aggregated yield, management, soil and monthly climate data. Thus, we define twelve study regions located in the Swiss Plateau (see Figure 1) under the following restrictions: (i) in each region and year enough historical yield and management records of different farms must be available[5]; (ii) for each region, a station of the new meteorological network of MeteoSwiss (SwissMetNet) should be located within the region or in vicinity; (iii) the distance between each point in a region and the SwissMetNet station should not exceed 35 km.

Figure 1: The twelve study regions
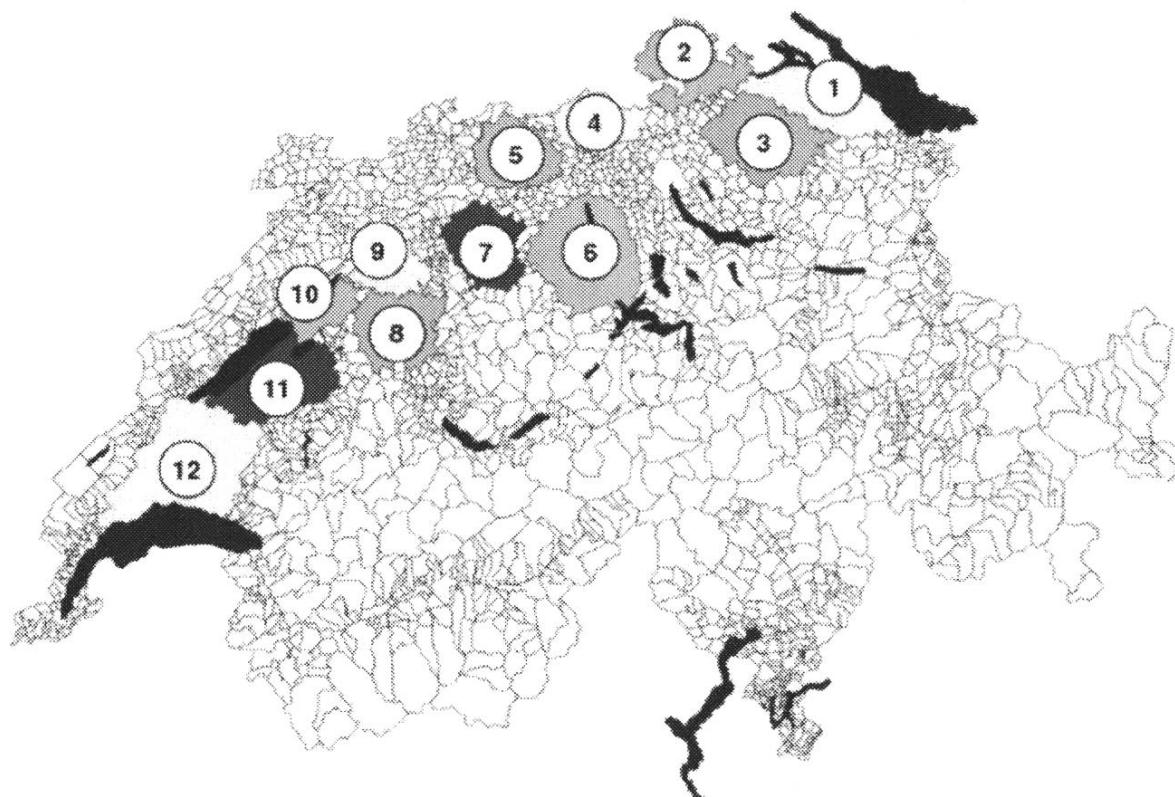
Source: Swisstopo, MeteoSwiss

Figure 1 shows the geographic location of the twelve study regions.

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[5] We apply a minimum of 25 farms per region and year in order to compute significant averages.

Historical yield and management data of the period 1990-2008 are obtained from the Farm Accountancy Data Network of the Agroscope Tänikon-Reckenholz (ART). In this study we consider fertilizer costs (CHF/ha), a specialization factor (dimensionless) and the amount of special direct payment for extensive wheat production (CHF/ha) as management variables. Since fertilizer costs rather should express the physical applied fertilizer amount than the financial costs, fertilizer costs are corrected by a national fertilizer price index[6]. Besides average fertilizer costs, also the specialization degree in crop production is assumed to be an important yield influencing management variable. In order to account for the farms' specialization degree, we apply a specialization factor which is computed for each region and year according to Equation 1.

(1)

$$SF_i = \left(\frac{GY_{PP_i}}{GY_{total_i}} \right) \cdot A_i$$

Where SF stands for the specialization factor, GYPP stands for the farm's gross yield generated through plant production [CHF/farm], GY_{total} represents the farm's total gross yield [CHF/farm], A stands for the farm's area of arable land [ha] and i for the year in the period 1990–2008.

Finally, we integrate as third management variable special direct payments for extensive wheat cultivation[7] into the regression model.
In a first step, yield levels, fertilization costs, the specialization factor and the special direct payments for extensive wheat cultivation are developed on farm level data. Then, in a second step, regional averages for each year are computed based on the farm level data by use of a trimmed mean, whereas the 10%-fraction of each end of the observations is discarded. The regional averaged management variables are generally applied as linear terms to the regres-

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[6] The national fertilizer price levels is obtained from the buying price index of agricultural means of production provided by the Swiss Farmer Union.

[7] In Switzerland, in the year 1991 ecological direct payments for extensive cereal production have been introduced. Farmers joining this ancillary payment scheme are not allowed to apply any fungicides, plant growth regulators, insecticides and chemical-synthetic stimulators of natural resistance to cereal crops or canola (BLW 2008).

sion model. In order to reflect the occurrence of decreasing marginal productivity, the fertilizer costs are not only integrated as a linear but also as a logarithmic expression into the regression model.

A region's climate conditions are expressed by the three monthly climate indices growing degree days (GDD), the modified moisture index (MMI) and the precipitation sums during a rain sensitive period of wheat. For each region, daily maximum and minimum temperature and daily global radiation values are obtained from one SwissMetNet station within or near the specific study region. Since in the Swiss Plateau precipitation shows larger spatial heterogeneity than temperature (Lehmann 2010), for each region a daily precipitation average based on the rain data of the region's assigned SwissMetNet and precipitation stations is computed. In total, daily precipitation data from 87 SwissMetNet and precipitation stations are used. The concept of GDDs assumes that phenological plant development is constant per degree of temperature between a base temperature (T_{Base}) and upper threshold temperature ($T_{cut-off}$) (Douglas 1998). By using GDDs instead of absolute temperatures, specific thermal requirements of wheat can be considered. In this study we compute the GDDs for wheat according to Equation 2.

(2)

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GDD = \begin{cases} \dfrac{T_{Max} + T_{Min}}{2} - T_{Base}, & if \ \dfrac{T_{Max} + T_{Min}}{2} \geq T_{Base} \ and \ \dfrac{T_{Max} + T_{Min}}{2} \leq T_{cut-off} \\[2ex] T_{cut-off} - T_{Base}, & if \ \dfrac{T_{Max} + T_{Min}}{2} > T_{cut-off} \\[2ex] 0, & if \ \dfrac{T_{Max} + T_{Min}}{2} < T_{Base} \end{cases}
$$

Where T_{Max} is the daily maximum temperature [°C], T_{Min} is the daily minimum temperature [°C] and T_{Base} and $T_{cut-off}$ are the base temperature [°C] and cut-off temperature [°C] of wheat. We apply $T_{Base}=3°C$ and $T_{cut-off}=22°C$ (Torriani et al. 2007).

The MMI can be computed by use of the potential evapotranspiration (PET) and precipitation (Willmott and Feddema 1992). The PET often has been used as the atmospheric water demand in studies investigating weather-yield relations (Chiemelewski and Köhn 1999; Esfandiary 2009; Werker and Jaggard 1998). By integrating the MMI as explanatory variable into the multiple regression model two advantages result. In first place, the MMI is symmetric about zero in the range -1 up to +1, whereas wet climates have positive values and dry climates have negative values. In second place, a high multicollinearity between temperature and precipitation values can be prevented by the combination of precipitation and evapotranspiration within one index. For this study we compute the MMI according to Willmott and Feddema (1992) as presented in Equation 3.

(3)

$$MMI = \begin{cases} \left[\dfrac{r}{E^\circ}\right] - 1, if\ r < E^\circ \\ 1 - \left[\dfrac{E^\circ}{r}\right], if\ r \geq E^\circ \end{cases}$$

Where MMI is the modified moisture index (dimensionless), r is the daily precipitation sum [mm·day^{-1}] and E° is the daily potential evapotranspiration [mm·day^{-1}]. In this study, the potential evapotranspiration (E°) has been computed after the Penman-Monteith method (Allen et al. 1998).

We include only monthly weather indices of the months in the vegetation period in the harvest year of wheat (February–August) in the regression model. Additionally, we define for wheat a rain sensitive period from March-August and compute for each year and region its precipitation sum. In order to express the non-linear relationships between weather and plant growth (Porter and Semenov 2005), all considered weather variables are incorporated as linear as well as quadratic expression. Finally, also a regional soil factor is used as independent variable in the multiple regression model. This factor is computed on the basis of the digital soil aptitude map of Switzerland provided by the Federal Office for Agriculture (FOAG). We use the classification of the digital soil map to derive a soil index (I_s) (see Lehmann 2010). Based on this classification

for each community of the twelve study regions an average soil index (I_m) according to the community's different area-weighted soils is computed. As in the regions the data records of different communities vary considerably among the years[8], a crop area-weighted soil factor (I_f) (see Equation 4) has been computed for each region and year and applied linearly and as a quadratic term to the regression model. The higher the soil factor I_f is, the more appropriate is a region's soil for agricultural production.

(4)

$$I_f = \frac{\sum_{k=1}^{n} I_{m_k} \cdot a_k}{\sum_{k=1}^{n} a_k \cdot 3}$$

Where If is the wheat area-weighted soil factor for a specific region and year. I_{mk} is the wheat specific mean soil index of the community k (k =1,2,...,n−1,n) and ak is the total area [ha] of wheat in the community k.

Finally, all explanatory variables are integrated into the multiple regression model as shown in Equation 5.

(5)

$$Y = \alpha_0 + \beta_1 \cdot GDD_{February} + \beta_2 \cdot (GDD_{February})^2 + \beta_3 \cdot GDD_{March} + \beta_2 \cdot (GDD_{March})^2 + \cdots + \beta_{11} \cdot GDD_{July}$$
$$+ \beta_{12} \cdot (GDD_{July})^2 + \beta_{13} \cdot GDD_{August} + \beta_{14} \cdot (GDD_{August})^2 + \beta_{15} \cdot MMI_{February} + \beta_{16}$$
$$\cdot (MMI_{February})^2 + \beta_{17} \cdot MMI_{March} + \beta_{18} \cdot (MMI_{March})^2 + \cdots + \beta_{29} \cdot MMI_{July} + \beta_{30}$$
$$\cdot (MMI_{July})^2 + \beta_{31} \cdot MMI_{August} + \beta_{32} \cdot (MMI_{August})^2 + \beta_{33} \cdot Prec_{SP} + \beta_{34} \cdot (Prec_{SP})^2$$
$$+ \beta_{35} \cdot Costs_{Fert} + \beta_{36} \cdot \log(Costs_{Fert}) + \beta_{37} \cdot DP_{Extensive} + \beta_{38} \cdot SF + \beta_{39} \cdot I_f + \beta_{40} \cdot I_f^2$$
$$+ \varepsilon$$

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[8] Note that not in every year the same farms are in the sample.

Where

Y:	Average wheat yield	[dt/ha]
GDD:	Monthly sum of growing degree days	[°C]
MMI:	Monthly sum of the modified moisture index	(dimensionless)
PrecSP:	Precipitation sum during a rain sensitive period	[mm]
$Costs_{Fert}$:	Average fertilizer costs	[CHF/ha]
$DP_{Extensive}$:	Average special direct payments for extensive wheat cultivation	[CHF/ha]
SF:	Average specialization factor	(dimensionless)
If:	Average soil factor	(dimensionless)

In order to select the most important yield determining factors among all included explanatory variables (see Equation 5), a stepwise backward variable selection by the Akaike Information Criterion (AIC) is used. The multiple of the number of degrees of freedom for the penalty is adapted, so that only significant (at a significance level of $\alpha = 0.05$) parameters remain in the model. The final developed regression model is tested on multicollinearity, heteroscedasticity and the residual's normal distribution. Moreover, also the model's stability is validated by a hold-out cross-validation[9].

2.2 Yield Projections under Climate Change Scenarios

For each of the used SwissMetNet stations future daily minimum and maximum temperatures, daily precipitation sums and daily solar radiation values are generated for a baseline period (corresponds to the time period of the input data 1990-2008), and for the two future periods 2011-2030 and 2046-2065 by use of the weather generator LARSWG[10]. For the two future periods the IPCC emission scenario A1B[11] is applied and the weather data is generated by use of the general circulation model Hadley Coupled Climate Model Version 3 (HadCM3). For each station and climate scenario, 500 years of daily weather

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[9] We choose randomly twelve years (training data set) and reestimate on the basis of this data set the coefficients of the explanatory variables. These newly estimated models are then applied to the remaining seven years (test data set) in order to estimate the fitted values of the crop yield levels. Finally, the residual standard error for each regression models based on the test data set is calculated. This procedure is repeated 500 times.

[10] The LARSWG is a stochastic weather generator, which has been specially designed for climate impact studies (Semenov and Barrow 1997). It has been tested for several climates and was found to perform better than other weather generators (Semenov et al. 1998).

[11] The A1B emission scenario expects a future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies whereas a balanced use of fossil and non-fossil energy sources is anticipated (IPCC 2000).

data are simulated. Yield projections under future assumed climate scenarios are made applying the simulated weather data on the developed regression model. Thereby, only climatic explanatory variables are changed. Management and soil variables on the other hand, are kept constant (ceteris paribus). Doing so, regional averages of all management variables as well as for the soil factor based on the data records of the period 1990-2008 are calculated and integrated as explanatory variables into the regression models. The relative changes in yield levels and yield variability are worked out by the comparison of the projected yields using weather variables generated under the baseline scenario with the projected yields using weather variables generated under one of the two future climate change scenarios.

3. Results

3.1 Multiple Regression Models

The multiple regression model of wheat explains by the selected 16 regressors[12] more than 76% of the yield variance (see Table 1). The GDDs in March, June and August are integrated by a positive linear and negative quadratic coefficient in the regression model. Therefore, in these months an inverted u-shaped relation between GDDs and yield levels can be observed. This indicates that neither too hot than too cold temperatures in March, June and August increase yield levels. Additionally, the GDDs in April and May have a significant impact on wheat yields, whereby high temperatures in April have a yield increasing effect, while high temperatures in May lead to a reduction of wheat yields. The MMI is crucial for wheat yields in the months of February, March, May and June. However, the water availability is only in March a yield limiting factor of wheat growth. In the other months the climate is generally too moistly for optimal wheat growth. The precipitation sum during a rain sensitive period, in turn, is not found to be a significant wheat yield influencing variable. As it could have been expected, wheat growth benefits from soil with a high apti-

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[12] Note that by applying the stepwise backward variable selection all selected regressors in the developed model were significant at a significance level of =0.05.

tude for agriculture. Moreover, regions where a high percentage of farms is specialized in crop production generally feature higher wheat yields. Though, the more special direct payments for extensive wheat cultivation farmers in a regions receive, the lower are the wheat yields in this region[13]. The two most important regressors are not weather but management variables, namely the specific crop payment for extensive wheat cultivation and the specialization factor. Together with the GDDs in June, these three regressors account for more than 40% of the model's total explained variance.

Table 1: Summary of regression model

Significant GDD Variables	$GDD_{March}(-)$, $(GDD_{March})^2(+)$, $(GDD_{April})^2(+)$, $GDD_{May}(-)$, $GDD_{June}(+)$, $(GDD_{June})^2(-)$, $GDD_{August}(-)$, $(GDD_{August})^2(+)$
Significant MMI Variables	$MMI_{February}(-)$, $MMI_{March}(+)$, $(MMI_{March})^2(-)$, $(MMI_{May})^2(-)$, $MMI_{June}(-)$,
Significant Management Variables	$SF(+)$, $DP_{Extensive}(-)$
Significant Soil Variables	$I_r(+)$
Most influential Regressors	(1.) $DP_{Extensive}$; (2.) SF; (3.) GDD_{June}
R-squared	0.7821
Adjusted R-squared	0.7641
Residual Standard Error	2.665
p-value of F-statistic	< 2.2e-16

Table 1 gives an overview of the regression model output. Conducting the stepwise backward variable selection only significant explanatory variables are kept in the model. The algebraic sign in parenthesis behind each regressor shows his influence on the regional wheat yield levels.

None of the regression model's presumptions of homoscedasticity, of normality of the residuals and of independence of the explanatory variables is rejected. Moreover, the residual standard error of the 500 regression models estimated during the hold-out cross validation increased on average by a factor of less than 1.9, which indicates that the developed regression model of wheat yields is robust.

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[13] Farmers joining the special payment for extensive wheat cultivation are not allowed to apply pesticides, fungicides and growth regulators, which reduces their potential yield levels (Finger 2010).

Figure 2 shows a comparison of the simulated yields with the observed yields in Region 8 (Seeland). Generally, in none of the study regions very large discrepancies between the observed and simulated regional wheat yields in the period 1990 – 2008 are found.

*Figure 2: Model performance in Region 8 (Seeland)*
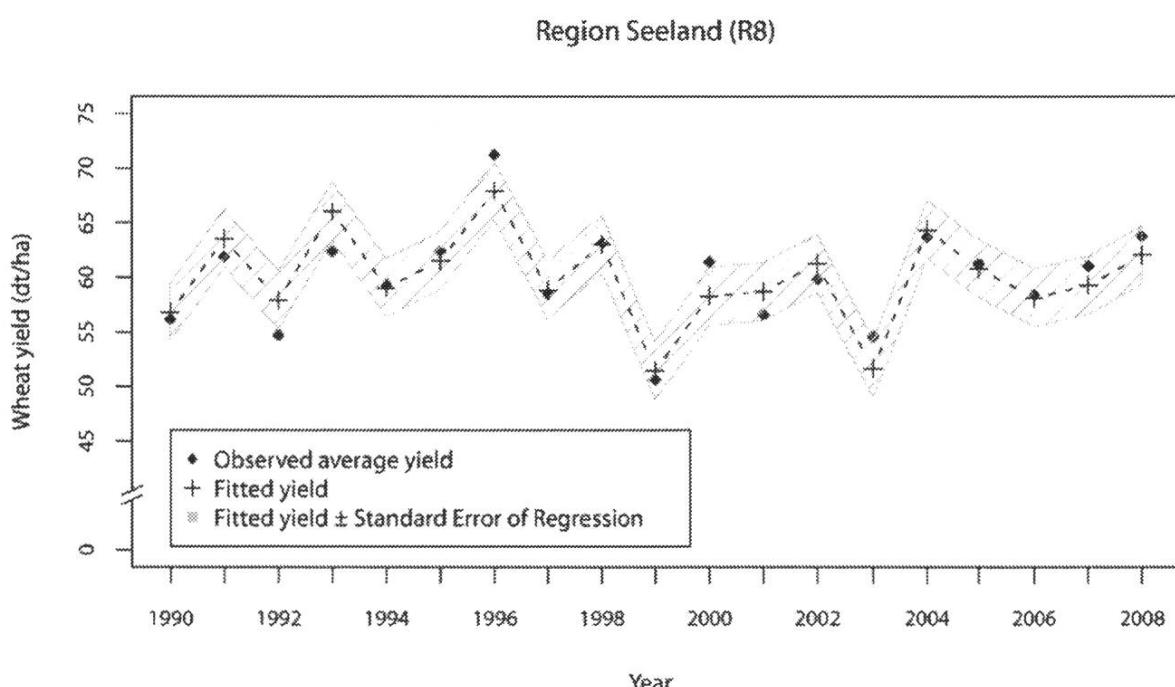
Figure 2 shows the performance of the developed model in Region 8.

3.2 Climate Change Impact on Yields

By means of the developed regression model and the generated weather data under the baseline scenario and under the A1B-2020, as well as the A1B-2050 scenario, impacts of climate change on wheat yield levels in each of the twelve study regions can be assessed (see Figure 3). Figure 3 indicates that climate change will decrease wheat yields in all regions. Under the climate change scenario A1B-2050 a decrease of average wheat yields between 4% and 10% is estimated for all regions. The highest reduction of wheat yields (more than 8%) occurs in Region 6 and Region 7 under the climate change scenario A1B-2050. Regarding Region 5, wheat yield is expected to decrease on average by

less than 5% under the scenario A1B-2050. For the scenario A1B-2020, the model anticipates in all regions a yield decrease of wheat of less than 2%. A comparison of the yield variance in the baseline scenario with the yield variance in the A1B-2050 scenario also allows an analysis of climate change impacts on the regional wheat yield variability. Figure 4 shows the expected change in variability of regional wheat yields for the A1B-2050 scenario. For most regions the model indicates an increase in yield variability under climate change. For instance, in Region 5 the model predicts an increase in yield variance of more than 35%. In the Region 7, however, our analysis results in a significant decrease in yield variability.

Figure 3: Relative wheat yield changes under climate change scenarios
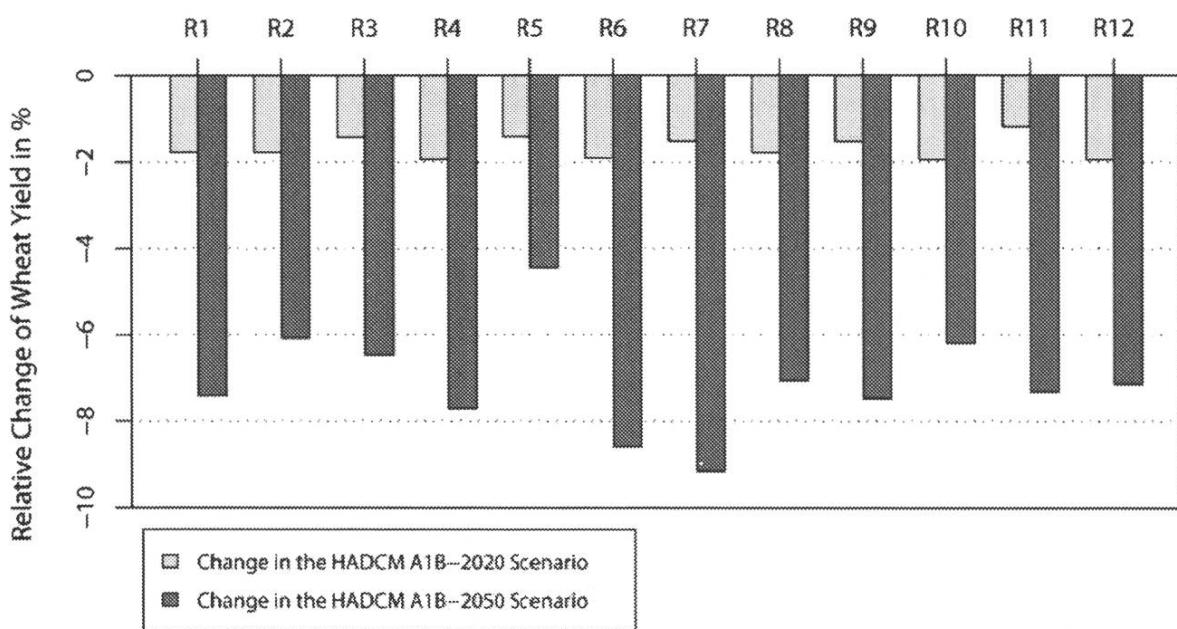

Figure 3 shows for each region the estimated relative mean changes in wheat yields comparing the simulated yields in the baseline scenarios with the generated yields in the A1B-2020 and in the A1B-2050 scenario, respectively.

Figure 4: Estimated changes in yield variability under the A1B-2050 scenario
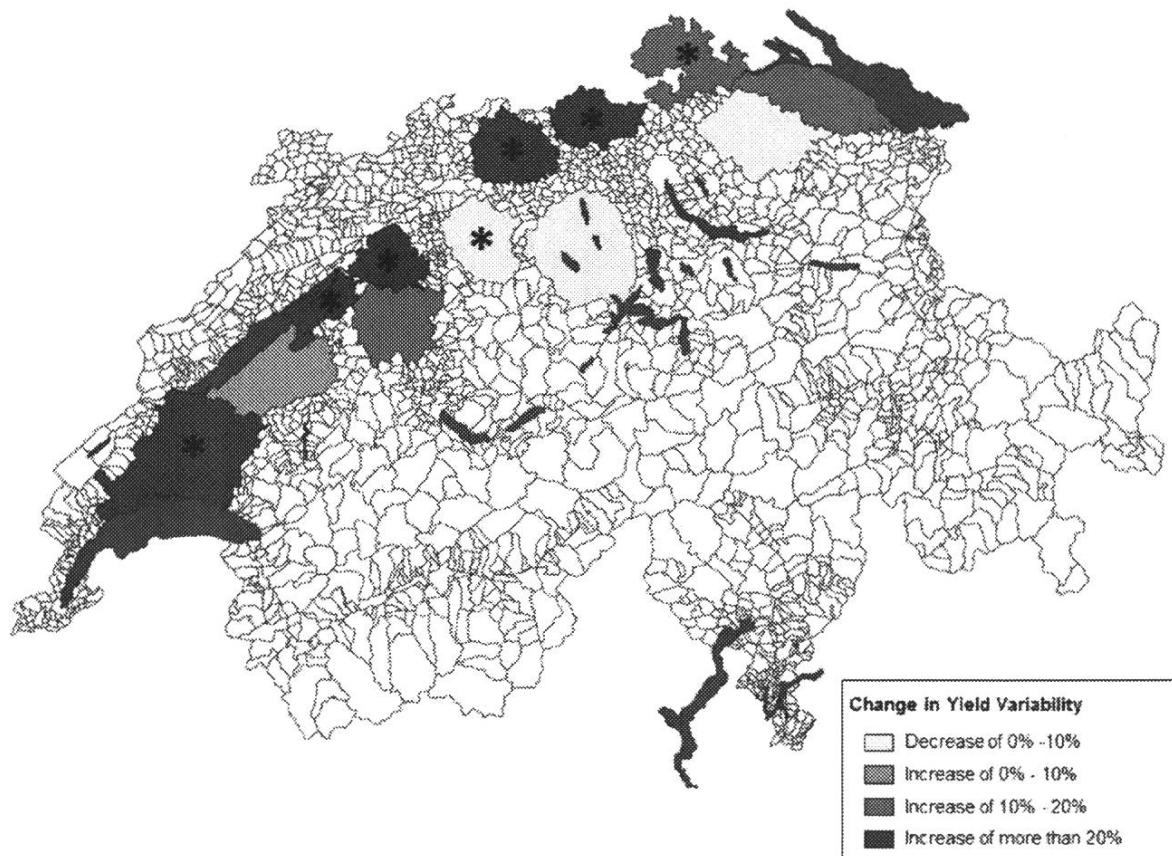
Source: Swisstopo

Figure 4 presents the changes in yield variability comparing the simulated regional wheat yield variances under the baseline scenario with the simulated regional wheat yield variances under the A1B-2050 scenario. In order to prove the significance of the estimated changes in yield variability, a one-sided Ansari-Bradley-Test has been conducted for each region. Regions with significant (significance level of $\alpha = 0.05$) changes in yield variability are shown by filled areas. Regions with a significant trend are marked with a *).

4.   Discussion

The most important regressor in the developed model is the amount of specific direct payments for extensive wheat cultivation. The high importance of this factor can mainly be traced back to the implementation of the contribution for extensive cultivation of cereals in Switzerland in the year 1991. As since then, farmers in Switzerland can decide if they want to apply for this special payment under the condition that no more pesticides and growth regulators are allowed in the wheat production, the regional yearly adoption rate of this specific crop payment varies considerably among time and space. During the first years after the implementation of this specific payment, only few farmers adopted to this program, while today a high percentage of farmers cultivates cereals under these ecological restrictions (Finger and El Benni 2011b). The non-use of pesticides and growth regulators, however, leads evidently to a decrease in cereal yields (Finger 2010). Regions, where a high percentage of farmers produces wheat under these restrictions, show generally lower yield levels[14]. The second most important regressor in the wheat model is the specialization factor, which is integrated with a positive coefficient. This indicates that farms which are more specialized in crop cultivation achieve generally higher wheat yields. Another important factor for the wheat yield levels are the GDDs in June. For the GDDs in June, like for the GDDs in March and August an inversed u-shaped relation can be observed. This shows that there is in the case of wheat an optimal temperature in March, June and August. Too hot or too cold temperatures in these months result in a yield decrease. The monthly MMI sum has except for March a negative impact on yield levels. This illustrates that droughts in summer months are currently not a relevant problem in the Swiss wheat cultivation.

Some similarities to our study can be detected in the multiple regression model of Landau et al. (1998) that consists of wheat yields and weather parameters recorded in UK as depending and explanatory variables, respectively. Firstly, in their study the monthly rainfall sums had generally a negative impact on yield levels (except for the rainfall in April) and secondly, temperature increases in

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[14] A significant negative linear relation resulted in an analysis of regional yearly wheat yields and regional yearly amounts of specific wheat payments.

midsummer leaded to a decrease in wheat yields (Landau et al. 1998). Flückiger
and Rieder (1997) observed that the monthly precipitation sums had in the
months of April-July a negative impact on wheat yields in Switzerland, while
the effect of precipitation in March was positive. This findings are in line with
our results, where the MMI in March is integrated with a positive and the MMIs
in May and June are integrated with a negative coefficient.

Wheat yields are expected to decrease under the climate change scenario A1B-
2050 by a percentage of 4-10%, whereas the yield variability of wheat increa-
ses in nearly all regions (except for Region 7) up to 34%. Regarding the changes
in the A1B-2020 scenario, only slight yield decreases can be observed, which
are in all regions smaller than 2%. The explanation, therefore, lies in the fact
that the A1B-2020 scenario corresponds to the period 2011 – 2030 during
which no large changes in climate compared to the baseline period (1990 –
2008) are expected. The simulated yield decreases for wheat under climate
change scenarios can mainly be explained with the excepted temperature in-
creases in the summer months. However, the model shows that the expected
decrease in precipitation in summer under climate change enhances the wheat
growing conditions in Switzerland. Torriani et al. (2007) predicted for the period
2071–2100 a reduction of the median of wheat yields of 26% at three diffe-
rent locations in the northeastern part of the Swiss Plateau under climate
change without considering the CO^2 fertilization effect. Additionally, they ex-
pected for the same time horizon and climate change scenario a decrease in
the variability of wheat yields of more than 30% (Torriani et al. 2007b). The
difference of the decrease in yield losses in the study of Torriani et al. (2007b)
compared to our results, can be explained by the different time horizons. In
this study, forecasts up to the period 2046-2065 have been made, while the
baseline period in the study of Torriani et al. (2007) has been compared to the
time horizon 2071-2100, where climate change is expected to be more pro-
nounced. However, the contradictory results in these two studies considering
the changes in the wheat variability are more surprising. A probable explanation
would be the fact that the two approaches used different methods in order to

simulate future daily weather parameters[15]. Flückiger and Rieder estimated a mean wheat yield decrease of 18% without considering the CO_2 fertilization effect under future climatic conditions in Switzerland. Ewert et al. (2005) investigated the impact of climate change on the European wheat productivity. They estimated for the year 2050 under the emission scenario A1F[16] a mean wheat productivity decrease of 2% without the consideration of CO_2 fertilization effect and technology improvements (Ewert et al. 2005).

Although regression models comprise tactical adaptation measures taken by farmers in the past to changes in climatic conditions, they do not account for systematic changes in management practices, which can be assumed to occur under hotter and dryer conditions. A sensitivity analysis of our results shows that yield losses in agriculture caused through climatic change can be reduced by several adaptation measures. Since not all crops will suffer at the same extent from climate change[17], a crop diversification at farm level can minimize weather-related risks in agriculture. Irrigation may become an important adaptation strategy in regions where water is already now a yield limiting factor (Fuhrer and Jasper 2009). However, Lehmann (2010) points out that irrigation is rather for tuber crops like potato and sugar beet appropriate, where a clear relation between the precipitation sum of a rain sensitive period and the crop yields can be found. Additionally, also changes in land use among the regions can mitigate negative climate change impacts on agricultural systems. For instance, Lehmann (2010) finds that potato yields will benefit from climate change in regions where they are nowadays rather a crop of minor importance (e.g. Region 6).

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[15] Torriani et al. (2007b) used a method, whereby observed daily data has been adjusted with monthly anomalies that reflect the full changes in the probability distribution of each of the climatic elements. In this thesis, in turn, a weather generator has been used in order to simulate future daily weather data.

[16] The A1F scenario expects a future world of very rapid economic growth, global population that peaks in midcentury and declines thereafter, and the rapid introduction of new and more efficient technologies, whereas the use of fossil-intensive energy sources is anticipated (IPCC 2000).

[17] Lehmann, 2010 showed that compared to barley, potato and sugar beet, wheat will suffer the highest yield losses in Switzerland under climate change. While barley yields are also assumed to decrease at a lower extent in all regions, the climate change impacts on potato and sugar beet yield levels can even be positive depending on the specific study region (Lehmann 2010).

5.　Conclusion

In this study we developed a multiple regression model using regional wheat yield levels in Switzerland in the period 1990-2008 as dependent variable and climate, management and soil indices as explanatory variables. We apply weather data generated under climate change scenarios to the regression model which allows us to make projections of climate change impacts on regional yield levels. We find that at a regional level more than 75% of the wheat yield variance can be explained by the regression model and climate change reduces in all considered regions the yield levels by less than 10%. However, this study did not take the CO^2 fertilization effect into account which is generally assumed to increase wheat yields (Amthor 2001).

Further research should test the effect of different climate change scenarios on wheat yields in Switzerland. Additionally, other regression methods (e.g. non-parametric regression models) should be used in order to compare our projections of climate change impacts on wheat yields with other predictions based on different statistical approaches.

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References

Allen, R. G., Pereira, L. S., Raes, D. and Smith, M., 1998. FAO Irrigation and Drainage Paper No. 56 Crop Evapotranspiration (Guidelines for Computing Crop Water Requirements). Technical Report, FAO -Food and Agriculture Organization of the United Nations.

Almaraz, J., Mabood, F., Zhou, X., Gregorich, E. and Smith, D., 2008. Climate Change, Weather Variability and Corn Yield at a Higher Latitude Locale: Southwestern Quebec. Climatic Change 88 (2), 187-197.

Amthor, J.S., 2001. Effects of Atmospheric CO^2 Concentration on Wheat Yield: Review of Results from Experiments Using Various Approaches to Control CO^2 Concentration. Field Crops Research 73 (1), 1-34.

BLW, 2008. Direktzahlungsverordnung. Technical Report, Bundesamt für Landwirtschaft (BLW) - Swiss Federal Office for Agriculture, Bern, Switzerland.

Boote, K., Jones, J., Hoogenboom, G. and Pickering, N., 1998. The CROPGROW Model for Grain Legumes. In Understanding Options for Agricultural Production. Kluwer Academics Publishers, 99-128.

Chmielewski, F. M. and Köhn, W., 1999. Impact of Weather on Yield Components of Spring Cereals over 30 Years. Agricultural and Forest Meteorology 96 (1-3), 49-58.

Diepen, C., Wolf, J., Keulen, H. and Rappoldt, C., 1989. WOFOST: A Simulation Model of Crop Production. Soil Use and Management 5 (1), 16-24.

Douglas, W. S., Lianne, M. D. and Lor, i.L.C., 1998. Phenological Temperature Response of Maize. Agronomy Journal 90, 73-79.

Esfandiary, F., Aghaie, G. and Mehr, A. D., 2009. Wheat Yield Prediction through Agro-Meterological Indices for Ardebil District. World Academy of Science, Engineering and Technology 49, 32-35.

Ewert, F., Rounsevell, M., Reginster, I., Metzger, M. and Leemans, R., 2005. Future Scenarios of European Agricultural Land Use: I. Estimating Changes in Crop Productivity. Agriculture, Ecosystems & Environment 107 (2-3), 101-116.

Finger, R., 2009. Climate Change Impacts and Adaption in Swiss Cereal Production: Integrating Biophysical and Economic Modeling. PhD Thesis, ETH Zurich.

Finger, R., 2010. Evidence of Slowing Yield Growth - The Example of Swiss Cereal Yields. Food Policy 35(2): 175-182.

Finger, R., Hediger, W. and Schmid, S., 2011. Irrigation as Adaptation Strategy to Climate Change: A Biophysical and Economic Appraisal for Swiss Maize Production. Climatic Change 105(3-4): 509-528.

Finger, R. and El Benni, N., 2011. Farmers' Adoption of Extensive Wheat Production - Determinants and Implications. 122nd EAAE Seminar «Evidence-Based Agricultural and Rural Policy Making: Methodological and Empirical Challenges of Policy Evaluation». Ancona (Italy), February 17-18, 2011.

Flückiger, S., and Rieder, P., 1997. Klimaänderung und Landwirtschaft: Ökonomische Implikationen innerhalb der Landwirtschaft und ihres Umfeldes aus globaler und regionaler Sicht. vdf Hochschulverlage AG an der ETH Zürich.

Frei, C., 2004. Die Klimazukunft der Schweiz - Eine probabilistische Projektion.
Fuhrer, J. and Jasper K., 2009. Bewässerung von Acker- und Grasland im heutigen Klima. AGRARForschung 16 (10), 396-401.

Goudriaan, J. and Zadoks, J. C., 1995. Global Climate Change: Modelling the Potential Responses of Agro-Ecosystems with Special Reference to Crop Protection. Environmental Pollution 87 (2), 215-224.

Hoogenboom, G., 2000. Contribution of Agrometeorology to the Simulation of Crop Production and its Applications. Agricultural and Forest Meteorology 103 (1-2), 137-157.

Iglesias, A. and Quiroga, S., 2007. Measuring the Risk of Climate Variability to Cereal Production at Five Sites in Spain. Climate Research 34 (1), 47-57.

Isik, M. and Devadoss, S., 2006. An Analysis of the Impact of Climate Change on Crop Yields and Yield Variability. Applied Economics 38 (2006), 835–844.

IPCC, 2000. IPCC Special Report on Emissions Scenarios. Intergovernmental Panel on Climate Change.

IPCC, 2007. Klimaänderung 2007: Zusammenfassungen für politische Entscheidungsträger. Intergovernmental Panel on Climate Change.

Keller, F. and Fuhrer, J., 2004. Die Landwirtschaft und der Hitzesommer 2003. AGRARForschung 11, 403-410.

Landau, S., Mitchell, R. A. C., Barnett, V., Colls, J. J., Craigon, J., Moore, K. L. and Payne, R. W., 1998. Testing Winter Wheat Simulation Models' Predictions Against Observed UK Grain Yields. Agricultural and Forest Meteorology 89 (2), 85-99.

Lehmann, N., 2010. Regional Crop Modeling: How Future Climate May Impact Crop Yields in Switzerland. Master's Thesis, ETH Zurich.

Lehmann, N. and Finger, R., 2010. Assessing Climate Change Impacts on Agricultural Systems: A Methodological Review. 117th EAAE Seminar on Climate Change, Food Security and Resilience of Food and Agricultural Systems. Stuttgart, Germany, November 25-27, 2010.

Lobell, D. B. and Field, C. B., 2007. Global Scale Climate -Crop Yield Relationships and the Impacts of Recent Warming. Environmental Research Letters 2 (1).

Osborne, T.M., Lawrence, E.D.M., Challindor, A. J., Slingo, J. M. and Wheeler, T. R., 2007. Development and Assessment of a Coupled Crop-Climate Model. Global Change Biology 13 (1), 169-183.

Patterson, D., Westbrook, J., Joyce , R., Lingren, P. and Rogasik, J., 1999. Weeds, Insects, and Diseases. Climatic Change 43 (4), 711- 727.

Porter, J. R. and Semenov, M. A., 2005. Crop Responses to Climatic Variation. Philosophical Transactions of the Royal Society B: Biological Sciences 360 (1463), 2021-2035.
Reidsma, P., Ewert, F., Boogaard, H. and van Diepen, K., 2009. Regional Crop Modelling in Europe: The Impact of Climatic Conditions and Farm Characteristics on Maize Yields. Agricultural Systems 100 (1-3), 51 - 60.

Ritchie, J., Singh, U., Godwin, D. and Bowen, W. 1998. Cereal Growth, Development and Yield. In Understanding Options for Agricultural Production. Kluwer Academics Publishers, 79-98.
SBV, 2009. Statistische Erhebungen und Schätzungen über Landwirtschaft und Ernährung, 2008. Technical Report, Schweizerischer Bauernverband.

Schlenker, W. and Roberts, M., 2008. Estimating the Impact of Climate Change on Crop Yields: The Importance of Nonlinear Temperature Effects. Technical Report, National Bureau of Economic Research.

Semenov, M. and Barrow, E., 1997. Use of a Stochastic Weather Generator in the Development of Climate Change Scenarios. Climatic Change 35 (4), 397-414.

Semenov, M., Brooks, R., Barrow, E. and Richardson, C., 1998. Comparison of the WGEN and LARS-WG Stochastic Weather Generators for Diverse Climates. Climate Research 10, 95-107. Spencer, B., 1983. Wheat Production, Milling and Baking. Chemistry and Industry (London), 591-596.

Stöckle, C. O., Donatelli, M. and Nelson, R., 2003. CropSyst, a Cropping Systems Simulation Model. European Journal of Agronomy 18 (3-4), 289-307.

Torriani, D., Calanca, P., Lips, M., Ammann, H., Beniston, M. and Fuhrer, J., 2007a. Regional Assessment of Climate Change Impacts on Maize Productivity and Associated Production Risk in Switzerland. Regional Environmental Change 7 (4), 209-221.

Torriani, D. S., Calanca, P., Schmid, S., Beniston, M. and Fuhrer, J., 2007b. Potential Effects of Changes in Mean Climate and Climate Variability on the Yield of Winter and Spring Crops in Switzerland. Climate Research 34, 59-69.

Werker, A. R. and Jaggard, K. W., 1998. Dependence of Sugar Beet Yield on Light Interception and Evapotranspiration. Agricultural and Forest Meteorology 89 (3-4), 229-240.

Williams, J., Jones, C., Kiniry, J. and Spanel, D., 1989. The EPIC Crop Growth Model. Transactions of the ASABE. 32 (2), 497-511.

Willmott, C. J. and Feddema, J. J., 1992. A More Rational Climatic Moisture Index. The Professional Geographer 44 (1), 84-88.

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